A NOVEL MODEL-BASED INDOOR POSITIONING USING SIGNAL STRENGTH

Kamran Sayrafian-Pour
Advanced Network Technologies Group
National Institute of Standard and Technology
Maryland, USA

Dominik Kaspar
Protocol Engineering Center
Electronics and Telecommunications Research Institute
Daejeon, Korea

ABSTRACT

A simple technique to estimate the position of a mobile node inside a building is based on the Received Signal Strength (RSS). In a previous publication, we investigated the feasibility of using circular array antennas and beamforming in order to enable an access point to estimate the position of a mobile inside a building. The approach utilized the two dimensional information (i.e. RSS for various azimuth directions) that is captured in a priori *measured* radio map. Generating these radio maps is not only extremely labor-intensive and time consuming but also sensitive to changes in the environment and possible source of interference. It would be interesting to find out if a deterministic propagation model such as ray tracing can be used to construct a radio map that effectively replaces the off-line manual measurements. In this paper, we investigate this issue and provide a novel positioning methodology that exhibits acceptable performance without the need for extensive set of measurements in the off-line mode. The performance for various parameters and building model accuracy will be presented and discussed.

I. INTRODUCTION

In recent years, technologies that find the location of mobile sources inside buildings are becoming an attractive area of research and development. A significant application of such technologies is in emergency situations where it is important to be able to locate or track the movements of the first responders inside closed environments. More commercial and public safety applications are also emerging every day.

A simple technique to estimate the position of a given source is based on the Received Signal Strength (RSS). RSS is attractive because it is widely applicable to wireless sensors or local area networks and does not require sophisticated localization hardware. The general philosophy in this approach is to establish a one-to-one correspondence between a given position and the average received signal strength from at least three access points with known locations. One such system that has been implemented on the existing wireless local area network infrastructure is RADAR [1]. There are two main phases in the operation of this system: an off-line phase (i.e. data collection or training phase) and an online phase (i.e. mobile position estimation). In the off-line phase, a "Radio Map" of the environment is created. A "Radio Map" is a database of locations throughout the environment and their corresponding received signal strengths from several access points. In the on-line phase, access points measure the received signal strength from the mobile, and then search through the Radio-Map database to determine the best signal strength vector that matches the one observed. The system estimates the location associated with the best-matching signal strength vector (i.e. nearest neighbor) to be the location of the mobile. This technique essentially calculates the L_2 distance (i.e. Euclidean distance) between the observed RSS vector and the entries in the set defined by the radio-map. It then picks the vector that minimizes this distance and declares the corresponding physical coordinate as the estimate of the mobile's location.

The main drawback of the RSS-based techniques such as RADAR is the need for a measurement-based training phase, during which the radio map of the environment is created. This map essentially contains the received signal strengths from all reference nodes throughout the environment. The process to generate a radio map is not only labor-intensive and costly but also very sensitive to changes in the environment and possible sources of interference in the building.

A simple alternative to generate the radio map for RSS-based positioning systems is using an appropriate propagation model instead of the actual measurements. For example, deterministic channel models such as ones based on ray-tracing are a good candidate for this problem. However, in these models, only simple high-level building information such as layout is used and other detail information about the environment such as the exact radio properties of the walls, and other obstacles affecting the RSS such as furniture are often ignored. The accuracy of the predicted signal strengths can be highly dependent on this detailed information which is almost impossible to capture in the model. Therefore, the performance of the positioning system will depend on the model's detail.

In a multipath environment, such as indoor, the mobile receives the transmitted signal from many directions due to possible reflections, diffractions and scattering phenomena. In [2], we showed that any information pertaining to the angular distribution of power can be used to increase the accuracy of a RSS-based localization methodology. In particular, an access point with an antenna that has beamforming capability can measure the signal strength in different directions to form a *Spatial Power Spectrum* (SPS) that can be used for position estimation. We showed that by using a more generalized and sophisticated radio map that contains received signal strength information from various directions, the system would have the capability of estimating the mobile position with fewer access points and higher accuracy.

In this paper, we extend our work in [2,10] and propose a positioning methodology that reduces the dependence of the system on the existence of an accurate radio map that has been obtained through rigorous measurement. The new methodology takes advantage of a ray-tracing tool that can

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create an approximate radio map of the environment. Assuming only one access point, this approach exhibits good performance even in presence of 4 dB of error in the estimated RSS. Increasing the number of access points will increase the robustness of the positioning system against imprecision in the radio map.

Section 2 will describe our proposed positioning approach. Modeling the error in the estimated RSS by the ray-tracing tool is discussed in Section 3. System performance is provided in Section 4 and finally concluding remarks and future plans are expressed in Section 5.

II. APPROACH

Consider a simple system consisting of an Access Point (AP) and a mobile node inside a building. Assume that the grid of points (x_i, y_i) $i = 1,2,....,N$ cover the entire building layout with a known resolution. If the mobile's coordinate is (x^*, y^*) then the objective of the positioning system is to estimate the mobile's location by finding the closest grid point to the mobile's coordinate. In other words, find 'k' where

$$k = \arg\min_i \left\|(x_i, y_i) - (x^*, y^*)\right\|.$$

Assume that the mobile node is a simple transmitter with an omnidirectional antenna and known transmit power 'P'. The AP is a receiver that is equipped with a circular array antenna with beamforming capability. In this way, the RSS in any given direction can be measured by electronically rotating the main lobe of the antenna pattern to the desired direction. Define $RSS_{AP}(\theta)$ to be the RSS from the mobile at the AP when the main lobe of its antenna is pointing at azimuth direction θ (Fig. 1a). Also, as shown in Fig. 1b, define $R_\theta(x_i, y_i)$ to be the received signal strength from the AP at the grid point (x_i, y_i) when the AP transmits a signal identical to the mobile (i.e. same power and frequency). If (x_j, y_j) happens to be the same as (x^*, y^*) (i.e. actual coordinate of the mobile node), then due to symmetry in the propagation of radio waves, we should have:

$$R_\theta(x_j, y_j) = R_\theta(x^*, y^*) = RSS_{AP}(\theta)$$

Now define $\hat{R}_\theta(x_i, y_i)$ to be the received signal strength from the AP at the grid point (x_i, y_i) estimated by a deterministic model such as ray-tracing. There will be a difference between this *estimate* and the actual value of the RSS. Define the "error" in the estimated RSS at grid point (x_i, y_i) to be the absolute value of this difference. In other words, if $E_\theta(x_i, y_i)$ denotes this error, then:

$$E_\theta(x_i, y_i) = R_\theta(x_i, y_i) - \hat{R}_\theta(x_i, y_i)$$

The value of this error in dB can be modeled as a *Normal* Random Variable with intensity σ and mean μ. A brief overview of the corresponding derivation has been provided in the Appendix.

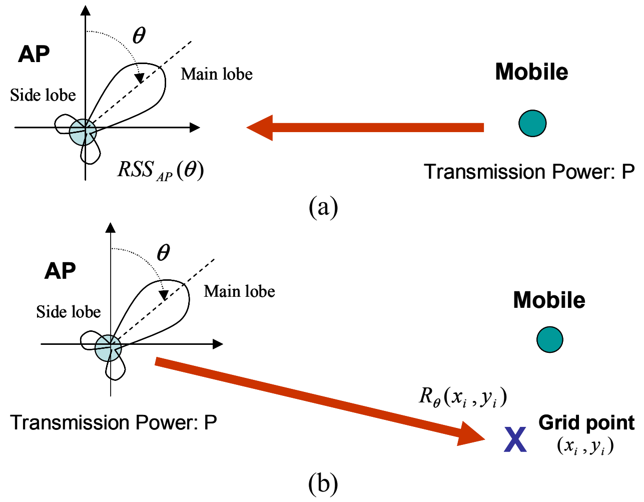

Fig. 1: RSS from (a) Mobile to AP (b) from AP to a grid point

$\hat{R}_\theta(x_i, y_i)$ $i = 1,2,....,N$ can be calculated by the ray-tracing model and the results can be saved in a database to form an *estimated radio map* of the environment.

Our approach in estimating the mobile's coordinate is to build a likelihood map for every θ, and then combine the information on all such maps to estimate the position of the mobile. A likelihood map, as the name implies, should highlight the likely positions of the mobile. Quantitatively, a likelihood map is basically a collection of Likelihood Scores (LS) for each grid point. Likelihood score at the grid point (x_i, y_i) is defined as follows:

$$LS_\theta(x, y) = \frac{1}{\left|R_\theta(x_i, y_i) - RSS_{AP}(\theta)\right|}$$

This is equivalent to:

$$LS_\theta(x_i, y_i) = \frac{1}{\left|\hat{R}_\theta(x_i, y_i) - RSS_{AP}(\theta) + E_\theta(x_i, y_i)\right|}$$

The mobile is likely to be close to grid points that have a high likelihood score. So, for each likelihood map, the set of grid points with the highest likelihood scores determine possible positions of the mobile inside the building. Figure 2 displays an example of a likelihood map for the building layout shown in Figure 4. The peaks in the 3-D plot display the likely positions of the mobile. By judiciously combining information for all likelihood maps, a single grid point can be found that represents the estimated position of the mobile. We propose the following approach to estimate the mobile's position. Define the Total Likelihood Score (TLS_A) at grid point (x_i, y_i) as:

$$TLS_A(x_i, y_i) = \frac{1}{\sum_{\theta} LS_{\theta}(x_i, y_i)}$$

The grid point with the highest TLS is the mobile's estimated position i.e. (x_k, y_k) where 'k' is

$$k = \arg\max_i TLS_A(x_i, y_i)$$

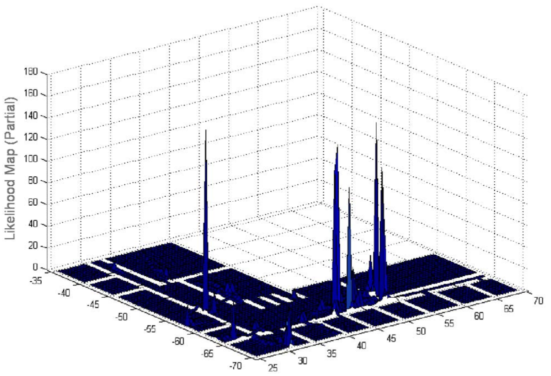

Fig. 2: Example of a likelihood map showing possible positions of the mobile

The total likelihood map is then the collection of total likelihood scores for all grid points. An example of a total likelihood map for the same layout is shown in Figure 3.

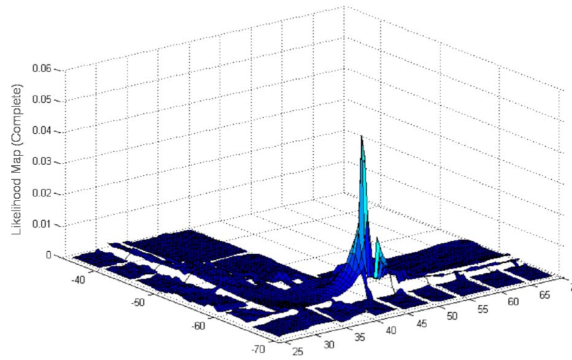

Fig. 3: Example of the total likelihood map showing the estimated position of the mobile

III. Modeling the Error in Estimated RSS

At indoor environments, the radio wave may travel through various obstructions such as walls, doors and furniture before reaching the mobile. Since, it is almost impossible to create a precise replica of the environment for the ray-tracing tool (including radio properties of all obstructions); it is valuable to have a model that can account for the difference between the average RSS estimates made by ray-tracing and actual measurement.

The difference in the average received signal strength (when measured in decibels) between the ray-tracing prediction and actual measurement (i.e. $E_{\theta}(x_i, y_i)$) can be modeled by a *Normal* random variable (see Appendix). We will assume that the mean of the corresponding distribution is zero; therefore, crude calibration of the ray-tracing tool might be needed to ensure this property. We refer to the variance of this normal distribution as *"error intensity"*. We will investigate the performance of the positioning algorithm for various error intensities.

In order to do so, we need to generate sample realizations of $E_{\theta}(x_i, y_i)$ for different values of error intensity. However, these realizations should be correlated for different θ. Consequently, we need a method to generate angle-dependent correlated Gaussian random variables. To do this, we follow the methodology outlined in [5,6]. If $X = [x_1, x_2, ..., x_N]$ is a random vector containing uncorrelated Gaussian random variables x_i, then random vector $Y = [y_1, y_2, ..., y_N]$ (with correlated Gaussian random variables y_i) can be generated by using a matrix C as

$$Y = C\,X\,.$$

C is a matrix of weight coefficients satisfying the following relation:

$$\Gamma = C\,C^T$$

In other words, C is the *Cholesky factorization* of Γ, where Γ is the correlation matrix of random vector Y i.e.

$$\Gamma = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1N} \\ \rho_{21} & 1 & \cdots & \rho_{2N} \\ \vdots & \vdots & \ddots & \\ \rho_{N1} & \rho_{N2} & \cdots & 1 \end{bmatrix}$$

ρ_{ij} is the angular cross-correlation function of the error in the average RSS estimates. We propose the following exponential decaying function to model the cross-correlation.

$$\rho_{ij} = e^{-\frac{|\theta_i - \theta_j|}{\theta_{cor}} \ln 2}$$

θ_i $i = 1,2,....,N$ is the direction of the main lobe of the antenna pattern at the AP. Given an angular rotation step-size of δ, we will have $N = 2\pi/\delta$. θ_{cor} is called the de-correlation angle and corresponds to the angle at which the correlation drops to 50%. We have considered a range of 10° to 45° for θ_{cor}. Similar distance-dependent correlation functions have been reported for outdoor systems [7,8].

IV. System Performance

To evaluate the performance of our proposed positioning algorithm, we used WiSE. WiSE (i.e. Wireless System Engineering) is a ray-tracing tool that has been developed and verified by Bell Laboratories [3,4]. For each θ, we simply used WiSE to estimate values of RSS for all grid points in order to build an estimated radio map of the environment. We made sure that the antenna pattern at the AP is the same pattern that is generated by beamforming with a circular array antenna. For the building layout shown in Fig. 4, we conducted extensive simulations to obtain the system performance. Transmission frequency was set at 2.4 GHz. We have studied the effect of many parameters such as grid resolution, de-correlation angle (θ_{cor}), rotation step-size (δ), number of APs, number of the array elements at the AP and error intensity; however, for brevity, we only present the main performance results in the following. Fig. 5 represents the average error in the estimated position versus number of the antenna array elements at the AP for various error intensities. Higher number of elements at the AP will increase the resolution of the beamformer; which along with an appropriately chosen δ can enhance the positioning accuracy. As observed in Fig. 5, average error of about 2 meters is achievable with 10 elements or higher even when there is 4dB of error in the estimated RSS by the ray-tracing tool.

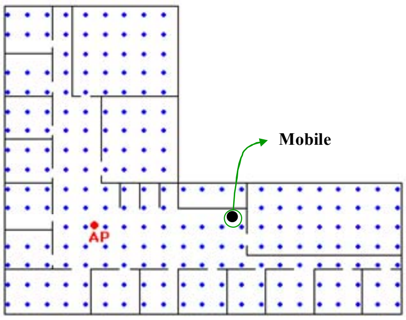

Fig. 4: Building layout showing the location of the mobile, AP and grid points

Fig. 6 displays the Cumulative Distribution Function (CDF) of position error for 500 randomly distributed mobile test location and various error intensities. For error intensities less than or equal to 4 dB, average error less than 3m is achievable with probability 0.9.

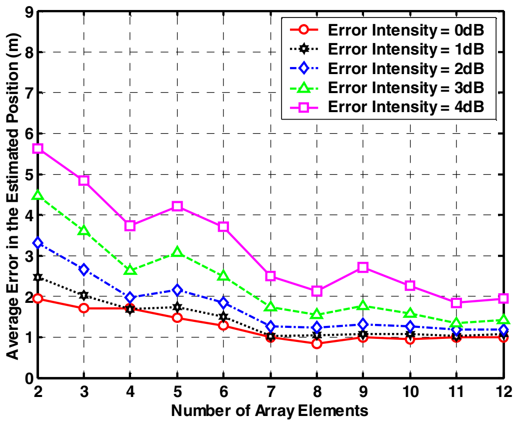

Fig. 5: Performance for various error intensities and array elements (θ_{cor} =10°, δ =5°, Grid Resolution=0.5 m)

For error intensities up to 4 dB, it seems that using only one access point can lead to reasonable accuracy for most applications. For higher error intensities, more number of access points can greatly help in reducing the average error in the estimate position. Fig. 7 demonstrates this point. As observed, using 3 access points for the layout in Fig. 4 leads to a very good performance even in the presence of 8dB modelling error.

We also investigated other approaches to calculate the Total Likelihood Score, e.g. TLS_B as shown below; however, we did not observe a significant change in performance.

$$TLS_B(x_i, y_i) = \frac{1}{\prod_{\theta} LS_{\theta}(x_i, y_i)}$$

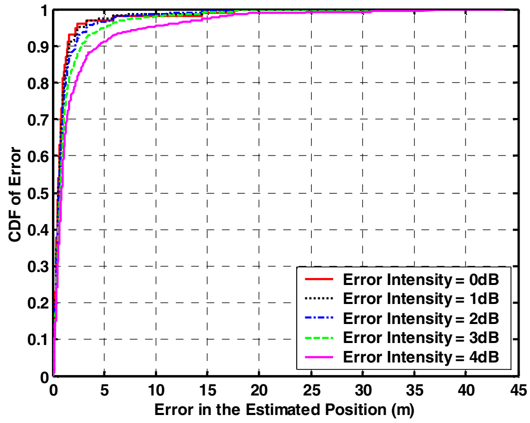

Fig. 6: CDF of error for various error intensities (θ_{cor} =10°, δ =5°, Grid Resolution=0.5 m, Array Elements=12)

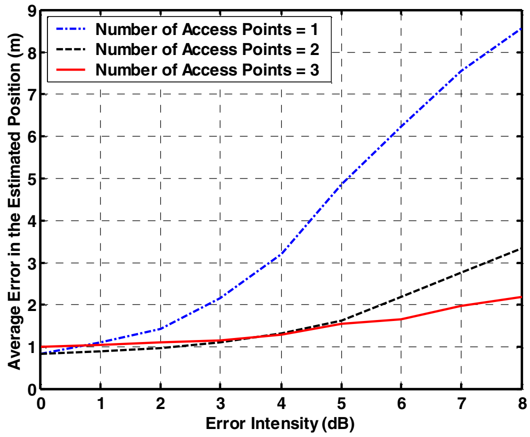

Fig. 7: Performance vs. error intensity for various number of access points (θ_{cor} =10°, δ =5°, Grid Resolution=0.5 m, Array Elements=12)

V. Conclusion

The underlying philosophy in this paper is that exploiting the information in the angular distribution of RF energy around a receiver could result in methodologies that are robust against propagation modeling error i.e. ray-tracing. Efficient and custom implementation of such ray-tracing tools integrated with appropriate positioning algorithm, such as the one proposed here, can lead to a complete system that is quickly deployable in any given environment.

Throughout this paper we have considered the case where the stationary access point with the circular array is the receiver and the mobile is the transmitter. If there are many transmitters available, a multiple access scheme has to be in place to differentiate between the signals of different transmitters. It is also possible to consider the case where the mobile is the receiver with circular array antenna capable of beamforming. In this case, many mobiles can estimate their locations simultaneously without the need for a multiple access scheme. More studies need to be done before such systems can have widespread applications in our daily life.

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VI. APPENDIX: MODELING THE RAY-TRACING PREDICTION ERROR

At indoor environments, the radio wave transmitted by the source node travels through different obstructions such as walls, doors, bookshelves, etc. Each one of these obstructions can be characterized by its own signal attenuation constant and thickness [9]. Suppose that the *ith* obstruction has an attenuation constant of α_i and thickness r_i, also suppose that the power of the wave entering (and exiting) an obstruction is E_{i-1} (and E_i) respectively, then

$$E_i = E_{i-1}\exp(-\alpha_i\, r_i)$$

If the knowledge of the exact values of α_i and r_i is not available, for example when using a propagation model like ray-tracing, then there will be an error in the estimated power of the signal passing through the obstruction.

$$\hat{E}_i = E_{i-1}\exp(-\alpha_i\, r_i + \varepsilon_i)$$

Where $\hat{E}_i$ is the estimated signal power after the obstruction and ε_i is the error component due to the partial knowledge of the attenuation constant and thickness. Since the signal passes through many obstructions (e.g. n), the total predicted RSS (i.e. $\hat{E}_n$) can be expressed by:

$$\hat{E}_n = E_0\exp(-\sum_{i=1}^{n}\alpha_i\, r_i + \sum_{i=1}^{n}\varepsilon_i) \qquad (1)$$

Also, since ε_i varies randomly from obstruction to obstruction, if we consider the number of obstructions to be large enough (i.e. $n\to\infty$), then by using the central limit theorem, we can state that the random variable $\Delta=\sum_{i=1}^{n}\varepsilon_i$ has a *Normal* distribution $p(x)$ such as

$$p(\Delta) = \frac{1}{\sqrt{2\pi\sigma_\Delta}}\exp\left(-\frac{1}{2}\left(\frac{x-m_\Delta}{\sigma_\Delta}\right)^2\right)$$

Where m_Δ and σ_Δ are the mean and variance of the random variable Δ. Now define the random variable Y by

$$Y = \log(\hat{E}_n) - \log(E_0\exp(-\sum_{i=1}^{n}\alpha_i\, r_i)$$

Y basically describes the difference (in dB) in the received power estimated by the ray-tracing model and the received power expected in reality. Using equation (1), we will get

$$Y = (\sum_{i=1}^{n}\varepsilon_i)\log e = \Delta\log e$$

Therefore, the mean, variance and probability density function of Y can be expressed by the following *Normal* distribution.

$$M_Y = \log m_Y = m_\Delta\log e,\quad \sigma_Y = \log\sigma_Y = \sigma_\Delta\log e$$

$$p(Y) = \frac{1}{\sqrt{2\pi\sigma_Y}}\exp\left(-\frac{1}{2}\left(\frac{x-M_Y}{\sigma_Y}\right)^2\right)$$

Therefore, the difference in the average received signal strength between the ray-tracing prediction and actual measurement can be modeled by a Lognormal distribution. Here, we will assume the mean M_Y to be zero, while we investigate the system performance for various error intensities σ_Y^2.